Does productivity growth fall after the adoption of new technology?

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Abstract

A number of theoretical models of technology adoption have been proposed that imply that measured productivity growth may initially fall and then later rise after the adoption of a new technology. This paper investigates whether or not this implication is a feature of plant-level data from the Colombian manufacturing sector. We focus on technology adoption embodied in new equipment. We find evidence that the effect of a large equipment purchase is initially to reduce plant-level total factor productivity growth.

Key Words: Productivity Growth; Equipment Investment; Technology Adoption

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Running Headline: Does productivity growth fall?

1 Introduction

A number of theoretical models of technology adoption have been proposed with the following feature. After a production unit adopts a new technology, not all the expertise in the old technology transfers to the new technology and there is a period of technology-specific learning. One implication of these theories is that measured productivity growth may at first fall and then later rise after adopting a superior technology.[1]

In this paper we provide micro-evidence on the question of whether productivity growth first falls and later rises after the adoption of new technology embodied in new equipment. We are motivated to address this question as micro-evidence on productivity growth is key for issues related to aggregate productivity growth dynamics. Consider an example. Greenwood (1996), Hornstein and Krusell (1996) and Greenwood and Yorukoglu (1997) hypothesize that an increase in the pace of embodied technological change is the cause of the aggregate productivity growth slowdown experienced by the majority of the advanced economies since the 1970's. A microeconomic mechanism behind this hypothesis is that existing production units experience a temporary fall in productivity growth after adopting new technology embodied in new equipment.[2] At the aggregate level, productivity growth could temporarily slow down when an increased fraction of production units make such investments. To evaluate such a hypothesis at a quantitative level, one would need micro-evidence on productivity growth dynamics after a production unit adopts new technology.

To address the question posed above, we identify the adoption of a new technology at a particular production unit with the purchase of equipment. In particular, we will say that those plants making equipment purchases that increase their real equipment stocks by more than a critical fraction are adopting new technology embodied in new equipment. A number of remarks are in order in regards to this assumption. First, an equipment purchase is precisely the mechanism of technology adoption emphasized in the literature. Second, the evidence in the papers by DeLong and Summers (1991, 1993) and Greenwood et al (1997) suggests that equipment investment may be a quantitatively important source of technology adoption.[3] Third, in plant-level data it is the case that investment displays a lumpy pattern at the plant level with the bulk of

[1] Zeckhauser (1968), Parente (1994, 1998), Klenow (1998) and Yorukoglu (1998) provide theoretical models with these features.

[2] We emphasize existing production units since in the data set that we explore the vast majority of equipment investment occurs at existing plants rather than at brand-new plants. Gort and Boddy (1967, p. 398) report a similar finding for the US manufacturing sector.

[3] DeLong and Summers (1991, 1993) show that the growth rate of labor productivity across countries is highly positively correlated with the fraction of equipment investment in GDP. Greenwood et al (1997) argue that the bulk of postwar US growth in labor productivity can be attributed to technological change

plants making little or no purchases of equipment in a given year but large percentage changes in the stock of equipment in other years.[4] Thus, our measure of technology adoption is consistent with the notion that technology adoption embodied in equipment occurs somewhat infrequently at the plant level. Lastly, we realize that our measure of technology adoption is far from perfect. Our reaction to this is two-fold. First, even if this measure is imperfect we will still be addressing an interesting question (i.e. Does productivity growth fall after a large equipment purchase?). Second, we regard it as a key issue for future research to focus on data sets that potentially allow one to distinguish between equipment purchases reflecting technology adoption versus those reflecting the acquisition of more capital of a technology known to the plant.

Our empirical strategy is straightforward. We focus on a data set of plants from the Colombian manufacturing sector. For each plant, we calculate total factor productivity (TFP) growth rates across time periods. We then regress the productivity growth of a plant on the current and past values of our plant-level measure of technology adoption, controlling for industry and/or time effects. We find evidence that productivity growth falls when a plant makes a large equipment purchase. More precisely, we find evidence that the effect of a large increase in a plant's stock of equipment is to reduce productivity growth by 3 to 9 percent in annual data. The fall in productivity growth is 3 percent when the criteria for a large equipment investment is 25 percent of the equipment stock, whereas it is 9 percent when the criteria is 100 percent of the equipment stock. We find no evidence to support the proposition that a plant's productivity level eventually rises so as to surpass the productivity level existing before the large equipment investment, after correcting for industry effects.

This paper is organized in four sections. Section 2 presents a number of background facts about the data set, plant-level productivity growth and plant-level investment in equipment. Section 3 presents our main results and then discusses interpretations of these results from the perspective of a few different models. Section 4 concludes.

1.1 Related Literature

To the best of our knowledge, there is only scattered micro-evidence bearing on the question that we address. We discuss work in three separate areas. First, there is a literature consisting of case studies by Baloff (1966, 1970), Russell (1968) and others in which plants from the US manufacturing sector have changed products or the production process and in which the level of productivity initially falls and then later

embodied in new equipment.

[4]This is documented by Doms and Dunne (1998) and Cooper et al (1999) using US data and by Ospina (1994) and Isgut (1996) using Colombian data. In section 2.3 of this paper we also provide evidence on this point.

rises. These studies are part of a large literature on learning curves. The focus of this literature has been to document the upside of the learning curve rather than any potential downside after a switch in technology. This is true, for example, of the well-known work of Bahk and Gort (1993) who estimate learning at new plants in the US manufacturing sector.[5]

Second, there is a literature on adjustment costs and on firm-level investment. Parts of these literatures have been surveyed by Chirinko (1993) and Dixit and Pindyck (1994). While some of the models presented in these literatures are potentially consistent with the findings of this paper, the empirical component of these literatures has not answered the question that we pose. With this said, we are aware of some work that is suggestive that firm investment in physical capital may be associated with falls in productivity. In particular, Pakes and Griliches (1984) regress firm-level, accounting profits on past investments. They find that accounting profit increases more strongly to investment lagged several periods than to more recent investment.

Third, there is a literature on information technology and productivity growth, reviewed in part by Brynjolfsson and Hitt (1998) and Yorukoglu (1998). Much of this literature focuses on the issue of whether there is an information technology productivity paradox. To the best of our knowledge, existing studies have not focused on characterizing falls in productivity growth at the time of an investment in information technology. However, with this said, some of this literature has found evidence for learning by doing in the years after an investment in information technology.

2 Background Facts

2.1 Description of Data Set

The Colombian Statistics Department (DANE) conducts an annual survey of plants in the Colombian manufacturing sector called the *Encuesta Anual Manufacturera*. DANE surveys all firms listed in the Industry directory. These firms are then required to report on all their plants with at least 10 employees. The data set covers the period 1974-1991. In a typical year the data set has between 6,000 and 8,000 plants.[6]

For each plant, data is collected on (1) employment and employee compensation, (2) capital inputs, (3) intermediate input, (4) production and (5) various other information.

[5]See Argote and Epple (1990), Jovanovic (1997) and Greenwood and Jovanovic (1998) for surveys of a number of distinct literatures related to learning.

[6]For a discussion of the methodology of the *Encuesta Anual Manufacturera* see DANE (1991). Research based on versions of this data set, some with and some without plant identification numbers, has been conducted by Roberts and Tybout (1996) and Isgut (1996) among others.

Employment is divided in six categories: proprietors, managerial, professional, blue collar, technicians and apprentices. Information on capital inputs is divided into five categories: buildings, machinery, office equipment, transport equipment and land. For each capital input there is data on book value, purchases of new and used capital, own production of capital, sales of capital, depreciation and revaluation. The data on book values for a particular year are end-of-period values. An important feature of the data set is that DANE assigns each plant a plant identification number. Thus, it is possible to track individual plants over time. This means that a plant-specific measure of productivity growth can be calculated.

Our analysis focuses on the collection of plants present in all years of the data set that are not excluded by any of the following two criteria.[7] First, we exclude any plant for which any of the data needed to calculate TFP growth rates are missing. This data includes employment and employee compensation for each type of labor input, book value of capital for the first year a plant appears in the data, investment data for each type of capital input, intermediate input consumption and gross production. In addition, we require strictly positive values for gross production, value added, capital services, intermediate input, total employment, total compensation and the real value of the stock of machines. Second, we exclude plants for which either the plant identification number is missing or repeated or for which the industry classification code is missing. After applying the above exclusion criteria, there are a total of 2125 plants in our data set each year and 31875 total observations on plants over the years $1976-90$. In any year of the data about half of these plants have less than 50 employees, whereas about 5 percent of the plants have 500 or more employees.

2.2 Productivity Growth Facts

This section characterizes some features of the distribution of total factor productivity (TFP) growth rates. The measurement of TFP growth rates is described in detail in Appendix A.1- A.2. Figure 1 plots the distribution of TFP growth rates in each year over the period 1976-90. Figure 1 shows that in each year (i) the median TFP growth rate is close to zero and typically positive, (ii) the TFP growth rate distribution is roughly symmetric with the vast majority of the plants having a TFP growth rate between 40 and -40 percentage points and (iii) a small percentage of plants (typically less than one percent) have a TFP growth rate either greater than 100 percent or smaller than -100 percent. This last finding is represented in Figure 1 by plotting all

[7] We focus on the balanced panel in order to minimize on measurement error in the calculation of TFP growth rates. We conjecture that plants that partially shutdown in a given year occur less frequently in the balanced than in the unbalanced panel.

plants with a growth rate of less than -100 percent at -1 and all the plants with a growth rate exceeding 100 percent at 1.[8]

We now comment on a number of other features of productivity growth rates in Figure 1. First, the variability of TFP growth rates is substantially greater at the plant level than what is observed in more highly aggregated data (e.g. industry or sectoral data). For example, TFP growth rates are typically between 0 and 10 percent when TFP growth rates are calculated for the Colombian manufacturing sector over the period 1976-90 using aggregate measures of outputs, inputs and factor shares. Second, although intuitively implausible, a straightforward application of Solow's growth accounting equation can produce TFP growth rates smaller than -100 percent. This can occur when input growth rates are large and positive and when output growth rates are not quite so large. We have examined a number of the cases of extreme negative TFP growth rates and have found that in these cases output increased by a couple of hundred percentage points whereas intermediate input increased at much greater rates.[9] The statistical methods employed in subsequent sections of this paper have been selected with these extreme observations in mind.

Insert Figure 1 Here

2.3 Equipment Investment Facts

We now document the distribution of plants by real equipment purchases as a fraction of the real equipment stock. Our measure of equipment consists only of machinery and thus does not include investment in office equipment, transport equipment or structures. Investment in machinery is by far the largest component of investment in physical capital. In particular, in all years machinery investment is between 70 and 80 percent of the combined value of the investment in machinery, office equipment, transport equipment and structures.

Figure 2 examines the distribution of equipment investment in the balanced panel. We find that the distribution of plants by equipment investment as a fraction of the equipment stock is similar across years. In a given year about 30 percent of the plants make no purchases of equipment and approximately another 30 percent make purchases of less than 10 percent of the value of their equipment stock. Due to depreciation, these plants will not expand their real equipment stocks. The last point that Figure 2 makes

[8] The maximum TFP growth rate is 60 (6000 percent) and the minimum is -287 (-28700 percent).

[9] Output is measured by gross production which measures both the value of finished goods produced as well as changes in the value of goods in the process of production. Thus, the extreme negative TFP growth rates are not due to not measuring goods in the process of production.

is that in any given year 5 to 15 percent of the plants make purchases that increase their equipment stock by 50 percent or more and 2 to 6 percent of the plants make equipment purchases that more than double their equipment stock.[10] In later sections we will say that plants making an equipment investment which increases the real equipment stock by $25, 50$ or 100 percent are adopting new technology embodied in equipment.

Insert Figure 2 Here

In the introduction we claimed that continuing plants (i.e. already existing plants) account for the bulk of the aggregate equipment investment in the Colombian manufacturing sector. Figure 3 provides some evidence on this point. Here we define a plant in the data set in a specific year t to be a continuing plant if it was in the data set in year $t-1$. Otherwise a plant in a specific year t is considered to be an entering (i.e. new) plant.[11] Clearly, this definition may understate investment at continuing plants as one could imagine defining a plant to be continuing if it were in the data set in any previous year. Nevertheless, using this definition, Figure 3 shows that on average over 90 percent of investment in machinery or in the sum of all types of reproducible physical capital occurs at continuing plants.[12]

Insert Figure 3 Here

3 Results

First, evidence is set out that bears on the question of whether the effect of a large equipment investment is to decrease measured productivity growth. Second, several theories of investment and productivity growth are presented to help interpret our findings.

[10] See Cooper et al (1995) for similar but less dramatic results for their sample of large plants in the US manufacturing sector. See Ospina (1997) and Isgut (1997) for a more detailed analysis of lumpy investment in Colombia. The upper tail in Figure 2 is very long with a very small fraction of plants making equipment investments that increase their equipment stocks by more than a factor of 100.

[11] Using this definition, over ninety percent of the plants in any given year are continuing plants.

[12] In 1982 continuing plants accounted for 76 percent of all investment. The bulk of this drop is due to a very large investment at one new plant in a capital-intensive industry. This does not appear to be due to any obvious recording or reporting error.

3.1 Productivity Dynamics

Our approach to determining whether a large equipment investment acts to contemporaneously decrease productivity growth is to estimate the parameters in equation (1). In equation (1) the variables y_t^i, z_t^i and D_{ij} are respectively the productivity growth rate, the technology adoption decision of plant i at time t and an industry dummy variable. The variable z_t^i takes the value 1 if the investment x_t^i of plant i at time t exceeds a critical fraction $\mathbf{x}$ of its equipment stock at time t (i.e. $x_t^i \geq \mathbf{x}$) and 0 otherwise. The variable D_{ij} takes the value 1 if plant i is in industry j and 0 otherwise.[13] Equation (1) states that productivity growth is the result of an industry effect ($\sum_j \alpha_j D_{ij}$) plus the effect of current and past technology adoption decisions ($\sum_k \beta_k z_{t-k}^i$) plus an error term (ϵ_t^i).

$$y_t^i = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i \tag{1}$$

We estimate the parameters in equation (1) by minimizing the sum of absolute errors (i.e. by least absolute deviation (LAD)). We note that when the error term has fatter tails than the normal distribution the statistics and econometrics literatures have stressed that there are non-linear estimators such as the LAD estimator that can have substantially lower variance than the ordinary least squares estimator.[14] Stated differently, the LAD estimator is not as sensitive as the ordinary least squares estimator to the presence of a small fraction of extreme observations on the dependent variable. Previously, the discussion related to Figure 1 highlighted the fact that measured productivity growth rates take on extreme values for a small fraction of the plants in our sample. These extreme observations lead the distribution of the error term to differ sharply from the normal distribution.

The benchmark results are listed in Table 1. The estimates of the parameter β_0 in Table 1 describe the effect of a large equipment investment on current productivity growth. The results indicate that the effect of a large equipment investment is to reduce plant-level productivity growth by 3 to 9 percent. The fall in productivity growth is larger for larger values of the critical fraction $\mathbf{x}$ of investment to the equipment stock

[13] Our industry dummies are at the three-digit level. There are 29 such industries in the data set.

[14] See Koenker and Bassett (1978) and the large literatures on robust estimation and quantile regression. Koenker and Bassett provide conditions under which quantile estimators, of which the LAD estimator is an example, are asymptotically unbiased and normally distributed. Key conditions for this result are that errors are independent and that the errors have positive density at the desired quantile. We use the S-Plus program rq to calculate point estimates and standard errors. This program implements the procedures described in Koenker and D'Orey (1987) and Koenker (1994).

used to define a large equipment investment. These point estimates are different from zero at the one percent significance level.[15]

Insert Table 1 Here

Table 1 also reports the regression results for the effect of large investments in the past on current productivity growth. The point estimates for the parameter β_1 indicate that the effect of a large equipment investment one year in the past is to decrease current productivity growth by 2 to 5 percent. These estimates are all significantly different from zero at the one percent level. The parameter estimates for lag lengths longer than a year are smaller in absolute value than the one year lagged effect and are typically negative. These estimates are often not significantly different from zero.

3.1.1 Two Robustness Checks

We focus on two questions: (1) Do the findings in Table 1 hold within specific industries? and (2) Are the findings in Table 1 sensitive to plausible magnitudes of unmeasured quality improvements in equipment?

Industry Results

To address the first question, we examine the four largest industries in the balanced panel as measured by the number of plants in that industry. For each of these industries we estimate by least absolute deviations the effect of a large equipment investment on productivity growth, controlling for year effects by means of time dummies, D_{it}. The four largest industries by SIC code are Food (311), Apparel (322), Other Chemical (352) and Metal Products (381). The findings listed in Table 2 are consistent with those in Table 1 in that the point estimates for the effect of a large equipment investment on current productivity growth is negative and in that the magnitudes of these effects are generally similar to those listed in Table 1. The standard errors of the estimates in Table 2 are larger than those in Table 1 due to the smaller number of observations. We conclude that the results in Table 1 tend to hold within industries and thus the process of pooling the data does not produce results that are not found in individual industries.

Insert Table 2 Here

[15] Ordinary least squares regressions on the data sets used in Table 1 also produce negative point estimates of the contemporaneous effect of a large investment on productivity growth that are significantly different from zero at the one percent level. The estimates of lagged effects are not significantly different from zero. These point estimates for the contemporaneous effect are larger in absolute value than the comparable LAD estimates but have substantially larger standard errors. These findings are robust to eliminating industry dummies or to allowing industry dummies to be time varying.

Quality Improvement Results

To address the second question, we note that the investment price index for equipment in Colombia makes no attempt to adjust for quality improvements. Substantial quality improvements in equipment have been documented by Gordon (1990). To examine the sensitivity to unmeasured quality improvements, the equipment capital for each plant in the data set is adjusted for quality improvements as follows. Let q_t index the quality level of investment in period t equipment. The old measure K_t and the new measure $\hat{K}_t$ of equipment capital stocks are calculated from the old measure of real investment I_t using the perpetual inventory method: $K_{t+1} = K_t(1-\delta) + I_t$ and $\hat{K}_{t+1} = \hat{K}_t(1-\delta) + I_t q_t$. All other aspects of the TFP growth calculations are as described in the Appendix.

The series for unmeasured quality improvements q_t is based on work by Gordon (1990, Table 12.2). He calculates that his quality-adjusted measure of the price of producer's durable equipment grows on average 3 percent slower over the period 1947-83 than the standard US price series that, like the Colombian series, does not attempt to adjust for quality improvements. Thus, we assume that q_t grows at 3 percent per year. Gordon's work is based on US rather the Colombian data. For this reason, the findings on this point should be viewed as being provisional and as providing potential magnitudes of the effects of unmeasured quality improvements on our results.

The results in Table 3 show that the main findings from Table 1 are robust to plausible magnitudes of unmeasured quality improvements in equipment. In particular, the contemporaneous effect of a large equipment purchase is to decrease productivity growth. These point estimates are significantly different from zero at the one percent level and the magnitude of the fall in productivity growth is slightly larger in absolute value than the comparable estimates in Table 1.

Insert Table 3 Here

3.2 Models of Investment and Productivity Growth

The results from the previous section call for a model which explains why equipment investment at the plant level is usually small but is sometimes very large as well as why plants with large equipment investments have lower productivity growth than plants in the same industry making no investment. A simple model in which the output Y_t of any plant within an industry is given by a constant returns to scale production function $Y_t = A_t F(X_t)$, where X_t is an input vector and A_t is an industry-specific technology level, cannot produce these results. In particular, in such a model productivity growth of any plant is given by the industry-specific growth in technology $\Delta A/A$. Thus, this model predicts that the regression coefficient β_0 in Table 1 is precisely equal to 0 since plants making large equipment investments have the same productivity growth as plants not making such investments.

Three specific models are described below which explain why investment is lumpy and why productivity growth is lower at plants making large equipment investments. Before presenting these models, we describe two measurement error stories that we do not think are driving the results in Table 1. First, one possibility is that we have mismeasured the capital input since the investment price indices make no attempt to account for quality improvement in equipment that is due to technical change embodied in new equipment. Previously, Table 3 examined the sensitivity of the benchmark results for plausible magnitudes of unmeasured quality improvements. The findings were that the effect of a large equipment investment on current productivity growth continue to be negative. Second, another possibility is that there are in reality several industries within our 4-digit industry classifications. In this case output growth will be mismeasured when true output prices have heterogeneous growth rates within a 4-digit industry. Following the line of argument in Appendix A.3, this type of measurement error is likely to bias the parameter estimates of β_0 in Table 1 upward not downward. Thus, this type of measurement error seems likely to further strengthen the case against the simple model described above.

Technology Adoption

Zeckhauser (1968) and Parente (1994, 1998) posit that an immortal craftsman periodically adopts superior technology. A version of their model is presented below, where (Y, X, A, Z) denote output, an input vector, a firm-specific technology level and firm-specific expertise with the current technology. The function F is constant returns to scale. When the craftsman adopts a superior technology (higher A) two things happen: first there is an immediate fall in expertise Z as not all the previous expertise transfers to the new technology and second Z later increases over time due to learning as long as the craftsman sticks to technology A. This story can easily be modified so that adopting a technology involves a purchase of capital specific to that technology.

$$Y_t = A_t Z_t F(X_t)$$

Machine Replacement

Recently the machine replacement problem (Cooley et al 1997 and Cooper et al 1999) has been advanced as an explanation of plant-level investment patterns and of lumpy investment in particular. A version of the model presented by Cooper et al (1999), which emphasizes equipment investment at existing plants, is presented below. Here (Y, X, A, Z) denote output, an input vector, an industry-specific technology shock and a plant-specific adjustment cost related to machine replacement. The function F is constant returns to scale. In periods where a machine is replaced $Z_t < 1$, whereas in periods without a machine replacement $Z_t = 1$.

$$Y_t = A_t Z_t F(X_t)$$

Stochastic Depreciation

Imagine that the machinery at a plant is subject to stochastic (i.e. "light bulb") depreciation.[16] For simplicity, suppose that all plants have precisely one machine which is essential for production. The machine works perfectly up to the point where it dies without the possibility of repair. The time of death of a machine is random. The production function for a plant is given below, where (Y, X, A) denote output, an input vector and an industry-specific technology shock. The function F is constant returns to scale. This model is the same as the machine-replacement model except that there is stochastic depreciation and there is no adjustment cost associated with machine replacement.

$$Y_t = A_t F(X_t)$$

3.2.1 Productivity Growth Implications

What are the total factor productivity growth implications of these three models? First, focus on the technology-adoption model. Following the Solow (1957) growth accounting calculation described in Appendix A.1, total factor productivity growth for a plant is $(\Delta AZ + A\Delta Z)/AZ$. Thus, total factor productivity growth (i) could fall after a switch in technology when the fall in expertise $(\Delta Z < 0)$ is sufficiently great to offset the technology improvement $(\Delta A > 0)$ and (ii) rises thereafter due to learning $(\Delta Z > 0)$ as long as the technology remains the same. In terms of the results in Table 1, the technology-adoption model is consistent with $\beta_0 < 0$ and $\beta_1, ..., \beta_K > 0$.

In the machine-replacement model, total factor productivity growth for a plant is also given by $(\Delta AZ + A\Delta Z)/AZ$. Thus, productivity growth within an industry for all plants making no machine replacements in two consecutive periods equals the amount of technological change $\Delta A/A$ at the industry level. Plants replacing machines have lower productivity growth than plants not replacing machines due to the proportional adjustment cost $\Delta Z < 0$. One period after replacement, productivity growth is higher than for plants making no replacement in the last two periods as $\Delta Z > 0$. In terms of

[16] A referee suggested that a discussion of this model might be helpful.

the results of Table 1, the machine-replacement model implies that $\beta_0 < 0, \beta_1 > 0$ and $\beta_2, ..., \beta_K = 0$, when a model period corresponds to a year.

In the stochastic-depreciation model, absent any errors in measuring outputs and inputs, total factor productivity growth is $\Delta A/A$ for all plants in a given industry. In terms of the results of Table 1, this model implies that $\beta_0 = \beta_1 = ... = \beta_K = 0$ since plants with and without large equipment investments have the same productivity growth after accounting for industry effects. Thus, with no measurement error this model is not consistent with the evidence presented. This conclusion needs to be reconsidered when one calculates capital input with the procedures described in Appendix A.1-A.2. The calculation of the capital input assumes that capital depreciates at a constant rate. This was made as there is no satisfactory information on true depreciation in the data set. What are the implications of the stochastic depreciation model? The model has the feature that capital input is always constant and thus the growth of capital input is zero. The constant depreciation assumption then implies that measured growth in the capital input is overestimated when a machine is replaced and underestimated by exactly the rate of depreciation at all other times. If this were the only consequence of this measurement error problem, then productivity growth would be underestimated for a particular plant when machines are replaced and overestimated by the depreciation rate times the cost share of the capital input otherwise. Under this assumption, the model implies that in a regression analysis $\beta_0 < 0$ and $\beta_1 = ... = \beta_K = 0$.

The analysis in the previous paragraph is not quite correct. The problem is that, given the procedures in the Appendix which impute cost shares using the data on capital stocks, errors in measuring the capital stock lead to errors in measuring the share of each factor input in total cost of production. In particular, the measured cost shares for a particular plant will have errors that depend on a plant's history of machine replacement. A consequence of this is that it is not a simple matter to determine what restrictions the stochastic-depreciation model offers on the signs of the parameters in Table 1.

3.2.2 Discussion

The three models of plant-level productivity growth just reviewed all seem capable of producing falls in productivity growth associated with large equipment investments. Thus, to separate these models using the findings in Tables 1-3 will involve using information on the response of current productivity growth to large equipment investments occurring in the past. At face value, the results in Tables 1-3 all state that a large investment one year in the past reduces current productivity growth (i.e. $\beta_1 < 0$). Thus, one might be tempted to conclude that on this basis the evidence presented is strongly against both the technology-adoption and machine-replacement models. We prefer to stress a different aspect of the evidence in Tables 1-3.[17] In particular, the evidence in Tables 1-3 provide no support for the proposition that a plant's productivity level eventually rises so as to equal or surpass the productivity level existing before the large equipment investment, after correcting for industry effects. Productivity dynamics with this feature are what one would expect to find if either the technology-adoption or machine-replacement model were producing the data.

4 Conclusion

The main findings of the paper are as follows: (1) Our best estimate is that the contemporaneous effect of a large equipment investment is to decrease a plant's total factor productivity growth by 3 to 9 percent in annual data. This decrease is larger for larger critical values for what constitutes a large equipment investment. (2) This finding holds within industries and is robust to plausible amounts of unmeasured quality improvements in equipment. (3) The bulk of investment in either equipment or all reproducible physical capital occurs at existing plants rather than at new plants.

We attach the following significance to these findings. First, the findings are inconsistent with models where all plants within an industry are affected by a common disembodied technology shock and/or by technological improvements embodied in new equipment. Second, if large equipment investments coincide with the adoption of new technology embodied in new equipment, then the findings imply that the adoption of new technology contemporaneously reduces total factor productivity growth. Third, we believe that the finding that the bulk of equipment investment occurs at existing plants has implications for future work. This finding suggests that the literature which attempts to quantify the implications of microeconomic models of equipment invest-

[17] One reason for not emphasizing the sign of the parameter estimate for β_1 has to do with how the growth rate of capital services is measured. Capital services, unlike output and all other inputs, cannot be calculated directly from expenditure data. Instead, capital services are imputed from data on capital stocks under the assumption that capital services for a particular type of capital are proportional to the capital stock in use in the period. Our best measure of capital in use is the *average* of beginning and end-of-period capital stocks. Thus, when there is a large, one-time increase in the capital stock in year t, our procedure implies that there is a large growth rate of capital services both in year t and $t+1$. This procedure seems appropriate when the increase occurs in the middle of the year, but leads to obvious bias when the increase occurs early or late in the year. We conjecture that this measurement problem may be behind the negative point estimates for β_1 in Tables 1-3. This seems plausible since we find that point estimates for β_1 are about .01 if one were to take the extreme position that the end-of-period capital stock is the most appropriate measure of capital in use. Such a measure also implies that point estimates for β_0 are even more negative than those reported in Table 1.

ment for aggregate productivity growth issues should concentrate on models where equipment investment occurs not only at new plants but also at existing plants.

We mention two directions to explore in future work. First, what is the effect on productivity growth of equipment purchases that reflect technology adoption versus those that merely reflect the acquisition of more capital of a technology known to the plant? This is a key question. To address this question a data set that allows such a distinction to be measured is needed. Doms et al (1997) describe a data set that is potentially promising in this regard. Second, it would be useful to see if the findings presented here are confirmed in data sets for other countries and time periods.

A Appendix

A.1 Measuring Productivity Growth Rates

Following Solow (1957), we assume that at each point in time a plant operates a constant returns to scale production function $Y_t = F(X_t, t)$ and that plants behave competitively. In this formulation, plants produce Y_t units of output using a vector of inputs X_t. Under the assumptions stated above, Solow derived the following growth accounting equation for calculating what is now called total factor productivity growth $\dot{F}/F$.[18] The equation states that at time t the rate of shift of the production function $\dot{F}/F$ at the current input vector equals output growth less a weighted average of the growth rates of the factor inputs. Weights are output elasticities (i.e. $\omega^n = F_n X^n / F$). Solow calculates these weights using factor shares of output, whereas we use cost shares. The cost share approach requires only competition in input markets rather than competition in input and output markets (see Hall (1991)).

$$\dot{F}/F = \dot{Y}_t/Y_t - \sum_n \omega_t^n \dot{X}_t^n / X_t^n$$

To calculate productivity growth at the plant level we first approximate growth rates with yearly growth rates as indicated below:

$$\dot{F}/F \doteq \Delta Y_t / Y_{t-1} - \sum_n \omega_t^n \Delta X_t^n / X_{t-1}^n$$

Next, we describe measurement. We measure Y by the value of nominal gross production measured in the data set divided by the industry-specific output price index.[19] We measure three separate factor inputs: labor, capital and intermediate input. We measure the real value of intermediate input by the nominal value of intermediate input measured in the data set divided by the price index for intermediate input. As we do not have a price series for intermediate input we use the GDP deflator for this purpose.

Our measure of labor input L_t at a particular plant at time t is the weighted sum of the number of employees L_t^j of type j at that plant at time t: $L_t = \sum_j w_t^j L_t^j$. The weights are chosen so as to measure the efficiency of labor input type j at the particular plant at time t. Thus, w_t^j is the total compensation per type j worker at the particular plant at time t divided by the average compensation per type 1 worker in the economy at time t. We choose blue collar workers to be type 1 workers. We note that this

[18] A dot over a variable denotes a time derivative.

[19] We deflate with four-digit output deflators. We have 51 distinct four-digit deflators. In some years four of these deflators have a zero price change. As we regard this as suspect, for these industries we set the price change equal to that of the GDP deflator in years where no price change is reported.

way of measuring labor input allows for plant-specific variation in the weight of each worker type while fixing the weight of type 1 workers in the entire economy at value of 1 each year. This allows for differences in labor efficiency of different worker types across plants arising from (i) differences in hours worked or (ii) differences in human capital.

We measure total capital services KS_t at a particular plant at time t as the sum of the capital services of each type of capital: $KS_t = \sum_j .5[K_t^j + K_{t+1}^j](\delta_j + r)$. This is the standard way that capital services is constructed from an underlying measure of the real capital stock of each capital type K_t^j (see Griliches and Jorgenson (1968)). Note that we use the average of the real value of the capital stock at the beginning of period t and period $t+1$ in order to calculate the measure of the capital stock most relevant for computing capital services during period t. We can distinguish five types of capital in our data set: structures, equipment, office equipment, transportation equipment and land. We indicate how we calculate K_t^j in Appendix A.2. We set the interest rate at $r = .05$ and the depreciation rates (δ_j) of structures, machinery, office equipment, transport equipment and land at $(4.61, 12.56, 13.32, 18.92, 0)$. With the exception of land which we have assumed does not depreciate, these estimates come from the work of Pombo (1998, Table 3.1) for the Colombian manufacturing sector.

We measure the weights ω_t^n as the average share of input n in total costs of a particular plant in period $t-1$ and t. As we observe the nominal cost of all inputs except capital services, some assumption needs to be made to calculate cost shares. We construct a common nominal price of capital services each year so that at this price the nominal value of gross production in a given year for all plants equals the nominal value of all input costs for all plants. This amounts to assuming that there are no aggregate profits each year for the entire manufacturing sector.

Following the procedures described above, we calculate productivity growth rates for each year starting from 1976. The first year is 1976 because the measure of the capital stock, described in Appendix A.2, can first be calculated at the beginning of 1975. This is due to the fact that the 1974 data on book value of capital are end-of-period values.

A.2 Measuring the Real Value of Capital

Our procedure for creating a series for each plant measuring the real value of type j capital stock at the beginning of the period is summarized in two equations:

1. First Year in Sample: $K_t^j = BV_t^j / p_t^j$
2. Subsequent Years: $K_{t+1}^j = K_t^j(1 - \delta_j) + (PN_t^j + PU_t^j + OP_t^j - S_t^j)/p_t^j$

K_t - real beginning of period value of capital

BV_t - beginning of period book value
PN_t - purchases of new capital
PU_t - purchases of used capital
OP_t - own production of capital
S_t - sales of capital
δ_j - depreciation rate of type j capital
p_t^j - Investment price deflator of type j capital

We have price deflators for structures, equipment (machines and office equipment) and transport equipment. The GDP deflator is used to deflate land. Depreciation rates are set at the values calculated by Pombo (1998).

A.3 Omitted Variable Bias- An Example

We show how mismeasured output prices can bias upwards the estimated effect of a large investment on productivity growth.

Step 1:

Let $\dot{A}/A$ and $\dot{\hat{A}}/\hat{A}$ denote true and measured productivity growth when the growth rate of gross production is measured correctly $\dot{Y}/Y$ and incorrectly $\dot{\hat{Y}}/\hat{Y}$. From Appendix A.1 we have the following:

$$\dot{A}/A \equiv \dot{Y}/Y - \sum_n \omega^n \dot{X}^n/X^n$$

$$\dot{\hat{A}}/\hat{A} \equiv \dot{\hat{Y}}/\hat{Y} - \sum_n \omega^n \dot{X}^n/X^n$$

When (i) $(p, \hat{p})$ denote different price indices, (ii) GP denotes nominal gross production and (iii) $Y = GP/p$ and $\hat{Y} = GP/\hat{p}$, then these measures are related as in the first equation below. Now let $y = \dot{\hat{A}}/\hat{A}$, let $\dot{A}/A$ be a linear function of z as posited in section 3 of the paper (i.e. $\dot{A}/A = \alpha + \beta z$) and let $w = (\dot{p}/p - \dot{\hat{p}}/\hat{p})$. The second equation below then follows from the first.

$$\dot{\hat{A}}/\hat{A} = \dot{A}/A + (\dot{p}/p - \dot{\hat{p}}/\hat{p})$$

$$y = \alpha + \beta z + \gamma w$$

Step 2:

Let productivity growth y_t^i, technology adoption (i.e. a large equipment investment) z_t^i and an omitted variable w_t^i be related as follows: $y_t^i = \alpha + \beta z_t^i + \gamma w_t^i + \epsilon_t^i$. The least squares estimate of β when w_t^i is omitted is given by β_1 below (see Greene 1993, p. 247):

$$\beta_1 \equiv Cov(y,z)/Var(z) = \beta + \gamma Cov(w,z)/Var(z)$$

Clearly, the estimate is biased upwards when $\gamma > 0$ and $Cov(w,z) > 0$. Since $\gamma = 1$ from step 1, the positive bias rests on the covariance between w_t^i and z_t^i. A positive covariance seems a plausible conjecture given the notion that big investments covary more strongly with true growth in industry price than with growth in a 4-digit measure of output prices.

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Table 1: Benchmark Results

$$y_t^i = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	-.037*					31875
	(.002)					
	-.034*	-.028*				31875
	(.002)	(.003)				
	-.034*	-.028*	-.004			29750
	(.002)	(.002)	(.002)			
	-.037*	-.029*	-.008*	-.001		27625
	(.002)	(.003)	(.003)	(.002)		
	-.037*	-.029*	-.009*	-.003	.004	25500
	(.003)	(.003)	(.003)	(.003)	(.002)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	-.054*					31875
	(.003)					
	-.052*	-.041*				31875
	(.004)	(.003)				
	-.053*	-.039*	-.006			29750
	(.003)	(.003)	(.003)			
	-.056*	-.041*	-.010*	-.005		27625
	(.003)	(.003)	(.003)	(.003)		
	-.056*	-.041*	-.013*	-.006	.001	25500
	(.004)	(.004)	(.003)	(.003)	(.003)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	-.087*					31875
	(.005)					
	-.086*	-.057*				31875
	(.006)	(.005)				
	-.086*	-.054*	-.012*			29750
	(.006)	(.006)	(.004)			
	-.091*	-.056*	-.016*	-.005		27625
	(.006)	(.007)	(.004)	(.004)		
	-.095*	-.055*	-.020*	-.008	.000	25500
	(.006)	(.006)	(.005)	(.005)	(.004)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level

Table 2: Industry Results

$$y_t^i = \sum_t \alpha_t D_{it} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	Industry	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	311	-.033*	-.014	-.005	-.009	.003	4020
		(.005)	(.005)	(.005)	(.005)	(.005)	
	322	-.031*	-.007	-.004	.003	.001	1764
		(.008)	(.007)	(.006)	(.008)	(.008)	
	352	-.010	-.021	-.014	.008	-.001	1860
		(.010)	(.015)	(.011)	(.013)	(.010)	
	381	-.026*	-.012	-.011	-.003	-.007	2208
		(.008)	(.007)	(.009)	(.009)	(.007)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	311	-.042*	-.025*	-.008	-.007	.006	4020
		(.013)	(.007)	(.009)	(.006)	(.006)	
	322	-.047*	-.027	-.009	-.001	-.003	1764
		(.013)	(.015)	(.009)	(.007)	(.008)	
	352	-.033*	-.021	-.009	.007	.001	1860
		(.012)	(.011)	(.013)	(.014)	(.010)	
	381	-.046*	-.035*	-.008	-.013	.002	2208
		(.009)	(.010)	(.010)	(.010)	(.009)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	311	-.075*	-.027	-.008	-.007	.005	4020
		(.012)	(.013)	(.008)	(.006)	(.008)	
	322	-.071*	-.026	-.024	-.002	.009	1764
		(.020)	(.016)	(.011)	(.016)	(.011)	
	352	-.036	-.050	-.015	.007	.002	1860
		(.033)	(.021)	(.021)	(.015)	(.019)	
	381	-.076	-.043*	.001	-.013	-.019	2208
		(.034)	(.013)	(.012)	(.013)	(.015)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level

Table 3: Quality Improvement Results

$$y_t^i = \sum_j \alpha_j D_{ij} + \sum_{k=0}^{K} \beta_k z_{t-k}^i + \epsilon_t^i$$

Independent Variable	β_0	β_1	β_2	β_3	β_4	Number of Observations
$z_t^i \equiv 1_{\{x_t^i \geq .25\}}$	-.040*					31875
	(.002)					
	-.038*	-.024*				31875
	(.003)	(.002)				
	-.037*	-.023*	-.003			29750
	(.002)	(.002)	(.005)			
	-.039*	-.024*	-.005	-.001		27625
	(.002)	(.003)	(.003)	(.002)		
	-.038*	-.023*	-.006	-.002	.005	25500
	(.002)	(.002)	(.003)	(.002)	(.002)	
$z_t^i \equiv 1_{\{x_t^i \geq .50\}}$	-.060*					31875
	(.004)					
	-.057*	-.035*				31875
	(.004)	(.003)				
	-.057*	-.032*	-.004			29750
	(.004)	(.003)	(.003)			
	-.060*	-.031*	-.007	-.004		27625
	(.003)	(.004)	(.003)	(.003)		
	-.061*	-.032*	-.009*	-.004	.003	25500
	(.003)	(.003)	(.003)	(.003)	(.003)	
$z_t^i \equiv 1_{\{x_t^i \geq 1.0\}}$	-.093*					31875
	(.006)					
	-.093*	-.035*				31875
	(.005)	(.005)				
	-.092*	-.045*	-.012*			29750
	(.006)	(.006)	(.004)			
	-.095*	-.046*	-.013*	-.003		27625
	(.006)	(.006)	(.004)	(.004)		
	-.097*	-.044*	-.015*	-.005	.001	25500
	(.007)	(.007)	(.004)	(.005)	(.005)	

standard errors are indicated in parenthesis

* indicates that coefficient is significantly different from 0 at the 1 percent level